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On-line estimation of state-of-charge of Li-ion batteries in electric vehicle using the resampling particle filter

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ABSTRACT

Accurate battery state-of-charge (SOC) estimation is important for ensuring reliable operation of electric vehicle (EV). Since a nonlinear feature exists in the battery system and particle filter (PF) performs well in solving nonlinear or non-Gaussian problems, this paper proposes a new PF-based method for estimating SOC. Firstly, the relationships between the battery characteristics and SOC are analyzed, then the suitable battery model is developed and the unknown parameters in the battery model are on-line identified using the recursive least square with forgetting factors. The proposed battery model is considered as the state space model of PF and then SOC is estimated. All experimental data are collected from the running EVs in Beijing. The experimental errors of SOC estimation based on PF are less than 0.05 V, which confirms the good estimation performance. Moreover, the contrastive results of three nonlinear filters show PF has the same computational complexity as extend Kalman filter (EKF) and unscented Kalman filter (UKF) for low dimensional state vector, but PF have significantly better estimation accuracy in SOC estimation.

Introduction

Electric vehicle (EV) powered by onboard batteries has advantages over traditional vehicle in energy saving and environment protection. However, these batteries are very sensitive to over-charge and deep-discharge. How to make the best use of batteries become increasingly important for EV. As one of the most important parameters for vehicular battery management system (BMS), the state-of-charge (SOC) directly affects battery life and battery system. Therefore, the estimation of battery SOC is a key point for BMS. Moreover, the uncertainty and complexity of the battery system add to the difficulty of SOC estimation.

The SOC is defined as the ratio of the remaining capacity to the nominal capacity at a given rate. The above definition is given in terms of the single cell. However, EV is powered by many battery packages in which some single cells are equally installed. In application, the battery packages are set in a big cell.

At present, there are two categories of methods for estimating SOC: physical methods and mathematic methods. In physical methods, SOC is estimated using physical properties of battery.

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- One of the physical methods is discharge test which is one of the most reliable methods for SOC estimation. However the method can only be applied in the laboratory since a test consumes too much time and the system can be forced to be interrupted during the test (Piller et al., 2001). Therefore, the method cannot estimate SOC dynamically.
- Measuring the physical properties of the electrolytes is another physical method to estimate SOC accurately. At the same time, the method is feasible only for lead-acid batteries where electrolytes can be measured (Piller et al., 2001).
- Open-circuit voltage (OCV) is widely used to determine SOC in many papers (He et al., 2012; Roscher and Sauer, 2011; Windarko and Choi, 2010). In order to achieve stable state of OCV, the batteries must be rest for a long time which may be more than 10 h. Therefore, the method is not practical for the running vehicles. In general, OCV is used combining with other methods discussed in Lee et al. (2008), Cheng et al. (2011), Snihir (2006).
- Impedance spectroscopy is a common method for electrochemical process in all battery applications. Impedance spectroscopy method for SOC estimation is described explicitly in Rodrigues et al. (2000), Huet (1998). However, this approach is strongly affected by temperature and requires some additional measurements which can only be statically obtained in laboratory test (Yoon et al., 2011). In (Coleman et al., 2007), the proposed model of SOC determination combines changing parameters such as terminal voltage, current load, and impedance spectroscopy.
- Internal resistance method is similar to the impedance spectroscopy method. However, the internal resistance method cannot precisely measure the cell resistance due to the influence of the time interval. The method applies to SOC estimation in post-discharge (Piller et al., 2001).
  The above methods are more suitable to do experiments in the laboratory and cannot meet requirement of SOC estimation for the running EV. With the development of EV, BMS has higher requirements for SOC accuracy. Therefore, various mathematic methods start to be used in SOC estimation.
- Ampere hour counting (Ah counting) is the most common technology for SOC estimation. So many papers (Lin et al., 2006; Coleman et al., 2007; Li et al., 2010; Ng et al., 2009) focus on using the Ah counting method or the improved Ah counting method to determine SOC. However, there are two issues for these applications: First, incorrect current accumulating for a long time can cause large error of SOC estimation. Second, when the batteries experience high temperature or strong current shock, the estimation error will increase. From these two points, we can see that Ah counting method is not suitable for high precision estimation.
- Linear model gives a mathematic relationship among SOC at various times, the current and the voltage. The model is applicable in the low-current condition and SOC changes slowly. In addition, it has high robustness in measurement errors and the initial conditions. The method is only developed in lead-acid battery.
- The Battery system is very complicated and certain relationships among the various parameters are unknown. Some researchers (Shen et al., 2005; Shen, 2010; Bi et al., 2012) start to focus on some intelligent methods such as artificial neural network (ANN). ANN considers the battery system as a black box and establishes an unknown relationship to estimate SOC by online training network. Another advantage of ANN is suitable for all battery applications.
- Kalman filter (KF) is a powerful intelligent method to accurately estimate the state of any linear-Gaussian system. Some papers (Bhangu et al., 2005; Plett et al., 2002a,b; Plett, 2004; Han et al., 2009; Vasebi and Bathaee, 2008; Charkhgard and Farrokhi, 2010) have introduced KF or extend Kalman filter (EKF) to estimate SOC. Though having been widely used in many non-linear systems, EKF has many constraint conditions such as requiring probability density function which follows Gaussian distribution.

As a nonlinear filter, particle filter (PF) is a novel and interesting class of algorithms to approximate the solution of nonlinear filtering problems. More importantly, PF should have significantly better estimation accuracy than EKF and unscented Kalman filter (UKF). In fact, the battery system is a strongly nonlinear and non-Gaussian system. At this point, PF is the right technology to estimate SOC. At present, even though application of SOC estimation in the field of PF has little discussed, Different from the previous paper (Schwunk et al., 2013), on the one hand, we estimate SOC according to give a suitable state space model of PF for battery system and identify the unknown parameters of the model. On the other hand, the Li-ion batteries in EVs are the research object and all experimental data of batteries are derived from the practical processes of EVs in operation instead of laboratory test.

This paper is organized as follows. Section 2 simply introduces the background of data collection. Section 3 proposes the battery model. Section 4 presents the parameters identification of this model. Section 5 shows the description of PF. Section 6 carries out experiments. Finally, Section 7 gives some conclusions and directions to the future work.

Background of data collection

To begin with we will provide a brief background on the data collection. Nowadays there are many applications of EVs such as electric taxis, electric buses, and electric sanitation trucks running in Beijing. Each EV has 120 Li-ion cells equally installed in 2 or 4 packages as power resource. The various on-line data collected by the BMS and the motor system can be transmitted to a data collection equipment in EV through the vehicular CAN bus. Moreover, the GPS system in the data collection equipment also collects GPS data such as position state, vehicle speed and mileage. All acquired data are packaged to be stored locally in the build-in flash memory of data collection equipment every 5 s. In addition, these data simultaneously packaged are wirelessly transmitted to the Service Center of Electric Vehicle by wireless GPRS communication

technology and stored in a large database in real time. One discharge process can produce thousands of packages. For example, if one discharge process takes 3 h, there will be about 1500 packages of data. This indicates the amount of data is very large.

As experimental data, unlike other battery parameters such as battery voltage and battery current, SOC cannot be measured directly, by definition, and can only be obtained by estimation. However in the BMS, SOC generally can be computed by combining the Ah counting and the capacity correction method. The acquired SOC has very high accuracy and can be considered as the true SOC to test experimental performance in Section 6.

Battery modeling

State space model is the basic of PF. The State space model consists of one state equation and one observation. As the discrete-time model is easy to be processed by computer, the state space model is designed in distribute forms in this paper. We use the discrete-time state space model to describe the battery system and develop the battery model.

The ultimate goal of developing the battery model is to use PF to accurately estimate SOC, so the battery model requires consideration of perfectly reflecting the dynamic and static characteristics of batteries. Due to vehicle types, battery systems, battery types and methods of research, there are many forms for the battery model. Therefore, firstly we need to determine the battery model.

State equation

The state equation is determined by the SOC definition in the paper. After the mathematical relation involving SOC is discretized by the Euler approximation for integration, the state equation is derived as Eq. (1)

$$z_{k+1} = z_k - \left(\frac{\eta \Delta t}{C_n}\right) i_k + w_k \tag{1}$$

where, state vector z_k is the value of SOC at time k. Input vector i_k is the instantaneous current at time k ($i_k > 0$ for discharge, $i_k < 0$ for charge). C_n is the nominal capacity. η is the Columbic efficiency ($\eta = 1$ for discharge and $\eta \leqslant 1$ for charge). Δt is the sampling interval. w_k is the process noise.

Observation equation

The observation equation needs to reflect the static and dynamic characteristics of the battery system. Many research studies such as electrochemical model, equivalent circuit model and RBF NN model have been recently carried out on this topic. The aims and applications vary from model to model. Considering the vehicle type (Hybrid-Electric Vehicle), the battery type (Li-ion), the data type (discharge) and the acquired data, we select the simplified electrochemical model (Plett, 2004) applying to Li-ion battery as the observation equation which is an analytical model and easy to estimate voltage or SOC.

$$y_k = k_0 - Ri_k - k_1/z_k - k_2 z_k + k_3 \ln(z_k) + k_4 \ln(1 - z_k) + \upsilon_k \tag{2}$$

where, y_k is the battery terminal voltage at time k, R is the battery resistance and k_0, k_1, k_2, k_3, k_4 are a set of parameters to fit Eq. (2) with the data well. υ_k is the measurement noise.

Above all, the structure of battery model consisting of Eq. (1) and Eq. (2) is overall described in Eq. (3).

$$\begin{cases} z_{k+1} = z_k - \left(\frac{\eta_i \Delta t}{C_n}\right) i_k + w_k \\ y_k = k_0 - Ri_k - k_1/z_k - k_2 z_k + k_3 \ln(z_k) + k_4 \ln(1 - z_k) + \upsilon_k \end{cases} \tag{3}$$

After the structure of the battery model is determined, the unknown parameters of the model k_0, R, k_1, k_2, k_3, k_4 not obtained from the acquired data need to be identified by the data sets of measured input and output signals.

Parameters identification

Common methods of parameters identification include least square method, maximum likelihood method and gradient calibration method. The least square method (LS) is most widely used considering the advantages of concise, rapid convergence and easy programming.

Least square method

If the observation equation is described by linear differential equation as

$$y_k = \varphi_k \theta + e_k \tag{4}$$

φ_k is the data vector at time k and y_k is the output vector at time k. θ is the parameter vector. e_k is the measurement noise at time k. For the observation equation, φ_k, θ and y_k are as follows. There is a set of L measured input and output data $\{z_k, i_k, y_k\}$. The definitions of z_k, i_k and y_k are shown in Section 3.

$$\varphi_k = \left[1, -i_k, -\frac{1}{z_k}, -z_k, \ln(z_k), \ln(1 - z_k)\right]^T \tag{5}$$

$$\theta = [k_0, R, k_1, k_2, k_3, k_4]^T \tag{6}$$

$$y_k = \left[1 \quad -i_k \quad -\frac{1}{z_k} \quad -z_k \quad \ln(z_k) \quad \ln(1 - z_k)\right]\theta + e_k \tag{7}$$

Define

$$Y_L = [y_1, y_2, \ldots, y_L]^T \tag{8}$$

$$\Phi_L = [\varphi_1^T, \varphi_2^T, \ldots, \varphi_L^T]^T \tag{9}$$

$$E_L = [e_1, e_2, \ldots, e_L]^T \tag{10}$$

Eq. (4) is denoted as the format of vector equation.

$$Y_L = \Phi_L\theta + E_L \tag{11}$$

The least square solution of Eq (11) is

$$\hat{\theta}_L = (\Phi_L^T\Phi_L)^{-1}\Phi_L^T Y_L \tag{12}$$

$\hat{\theta}_L$ is the vector of final estimated parameters based on LS estimation method. In order to achieve higher accuracy of SOC estimation, the proposed battery model should on-line accord with practical battery system. But since computing the inversion of matrix Φ can make the amount of calculation and memory capacitance substantial, the parameters do not apply to be on-line identified by LS. In addition, the increasing amount of sample data may lead to the phenomenon that the estimated value cannot be modified by new measured data. By way of solving the two problems, recursive least square with forgetting factors (RFF) rather than LS is suitable for on-line identify the unknown parameters.

Recursive least square with forgetting factors

The idea of RFF is that according to apply forgetting factors old data have less influence and new data play a bigger role. Assume a new set of measured data $\{z(L+1), i(L+1), y(L+1)\}$ are used in the system, so the new data matrices are respectively $\Phi_{L+1} = \begin{bmatrix} \lambda\Phi_L \\ \varphi_{L+1}^T \end{bmatrix}$ and $Y_{L+1} = \begin{bmatrix} Y_L \\ y_{L+1} \end{bmatrix}$. λ, $0 < \lambda \leqslant 1$ is the decay factor. Then, the vector of new estimated parameters is obtained from Eq. (12).

$$\hat{\theta}_{L+1} = (\Phi_{L+1}^T\Phi_{L+1})^{-1}\Phi_{L+1}^T Y_{L+1} = \hat{\theta}_L + G_{L+1}[y_{L+1} - \varphi_{L+1}^T\hat{\theta}_L] \tag{13}$$

where,

$$G_{L+1} = \frac{P_L\varphi_{L+1}}{\rho + \varphi_{L+1}^T P_L \varphi_{L+1}} \tag{14}$$

$$P_{L+1} = [\Phi_{L+1}^T\Phi_{L+1}]^{-1} = \frac{1}{\rho}[I - G_{L+1}\varphi_{L+1}^T]P_L \tag{15}$$

Define $\rho = \lambda^2$. P_{L+1} are the covariance matrix and G_{L+1} is the mathematical expression. The steps of parameters identification are simply described as follows.

- Step 1: set initial value P_0, $\hat{\theta}_0$.
- Step 2: according to Eq. (13)–(15), update $\hat{\theta}_{L+1}$, P_{L+1} and G_{L+1}.
- Step 3: L is increased by itself and return to step 2. Eq. (16) is considered as the criterion of ending identification. Then, the parameter values can well reflect the characteristic of the system. $\hat{\theta}_{L+1}(i)$ is the ith element of θ and ε is the given precision. $\hat{\theta}_{L+1} = \hat{\theta}_{L+2} = \cdots = \hat{\theta}_{L+n}$.

$$\max_i \left|\frac{\hat{\theta}_{L+1}(i) - \hat{\theta}_L(i)}{\hat{\theta}_{L+1}(i)}\right| < \varepsilon \tag{16}$$

There are two methods to set initial value (P_0, $\hat{\theta}_0$):

(1) Take the first m sets of data to calculate $\widehat{P}_m$ and $\hat{\theta}_m$ by LS method. $\widehat{P}_m$ and $\hat{\theta}_m$ are considered as initial value.
(2) Set $\hat{\theta}_0 = 0$ and $P_0 = \sigma^2 I$. σ^2 is an especially big number.

An example of parameters identification

A didactic example is included to illustrate the computational procedure of parameters identification. In the example, the experimental data are collected from one discharge process of one vehicle running from 7:37 am to 12:58 am on May 25, 2011. The identifiable result of each parameter is shown in Fig. 1.

In order to more quickly identify the final parameters, the paper chooses the first methods to set the initial parameters (P_0, $\hat{\theta}_0$). The initial parameters are set in the initial phase from the start to the thirtieth minute. Fig. 1 shows all parameters have less charge in the initial phase compared to other phases. After 30 min, the parameters are updated continuously until the 63rd iteration (101 min). The final identifiable result of each parameter is respectively shown in Table 1.

In order to test whether these estimated parameters match the model, inputting the sets of data and the estimated parameters in the observation equation, we estimated voltage. The relative error (RE) and the root-mean-square relative error (RMSRE) is used as two performance index.

$$\mathrm{RE} = \frac{|y_k - \hat{y}_k|}{y_k} \tag{17}$$

$$\mathrm{RMSRE} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(\frac{y_k - \hat{y}_k}{y_k}\right)^2} \tag{18}$$

where, y_k is the true value, $\hat{y}_k$ is the estimation value. The comparison results between the estimated voltage and the true voltage are shown in Figs. 2 and 3. The estimated curve and the true curve have similar trend. RMSRE is 0.0052. Most of the RE is below 0.01 and the maximum error is 0.024 which occurs instantaneously. These errors mainly caused by the process noise are comparatively small and within the engineering allowance. So, our proposed battery model and estimated results are verified through experimental study.

Results of identification experiments

The condition of each EV varies every day, even for the same vehicle type and the same battery type. In order to evaluate real-time performance and the accuracy of identification, parameters should be on-line identified. So, the results can only be applied to the current discharge process.

The more results of the experiments of identification are also presented to verify the efficiency of RFF. The experimental data are collected from ten discharge processes of the same vehicle. The error results are shown in Table 2.

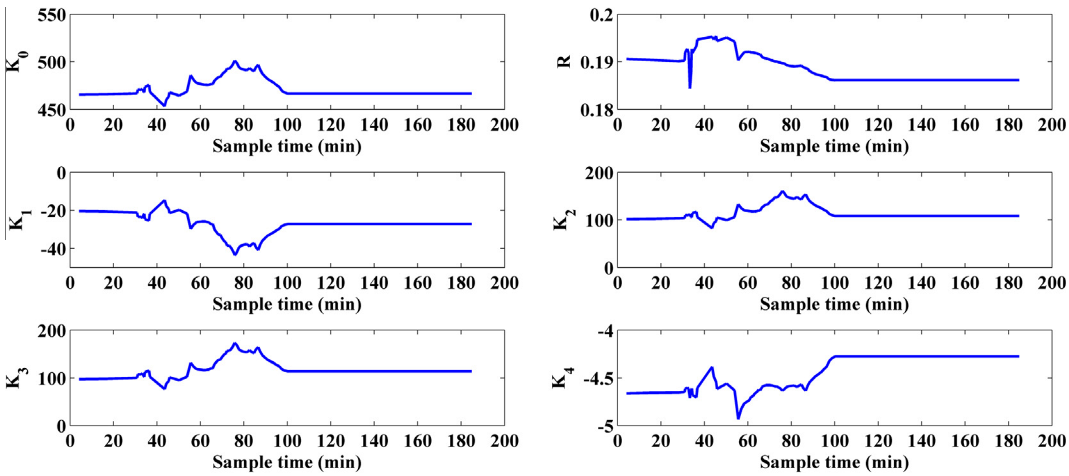

Fig. 1. Results of parameters identification (one discharge process).

Table 1
The final estimated parameter values.

k_0	R	k_1	k_2	k_3	k_4
466.57	0.187	−27.25	108.16	113.94	−4.28

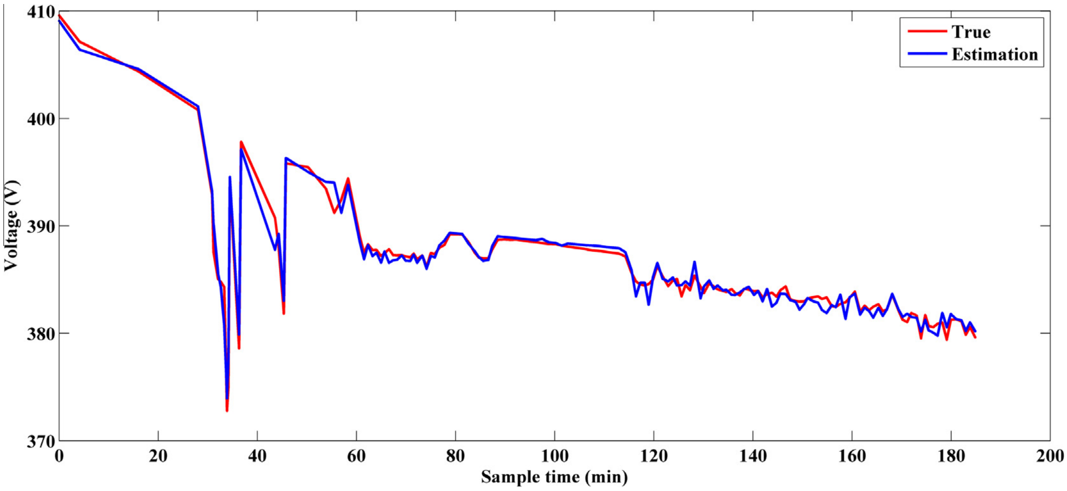

Fig. 2. Voltage estimation.

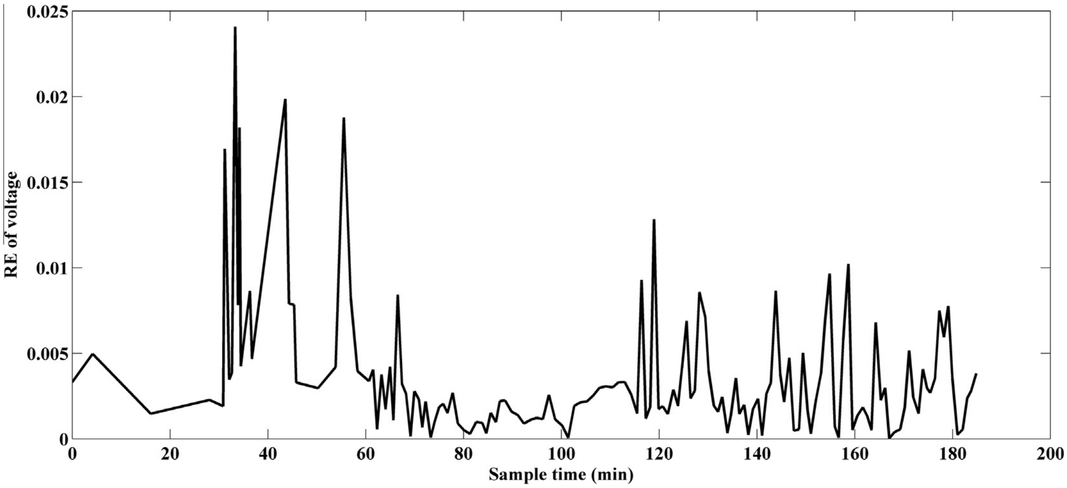

Fig. 3. The RE of voltage estimation.

Table 2
The error results.

Discharge processes	Data collection period	RMSRE	Max RE
1	2012-07-20 07:48:28 2012-07-20 14:02:35	0.0055	0.0189
2	2012-07-21 08:55:23 2012-07-21 14:17:20	0.0070	0.0262
3	2012-07-23 08:21:06 2012-07-23 13:23:07	0.0050	0.0209
4	2012-07-25 08:05:04 2012-07-25 14:50:01	0.0061	0.0319
5	2012-07-26 05:59:40 2012-07-26 12:52:50	0.0038	0.0115
6	2012-07-27 15:35:45 2012-07-27 18:47:06	0.0074	0.0315
7	2012-07-28 11:08:22 2012-07-28 15:21:48	0.0087	0.0209
8	2012-07-29 08:29:18 2012-07-29 13:08:04	0.0045	0.0179
9	2012-07-30 08:31:08 2012-07-30 12:19:43	0.0069	0.0230
10	2012-07-24 09:59:07 2012-07-24 15:18:39	0.0067	0.0181

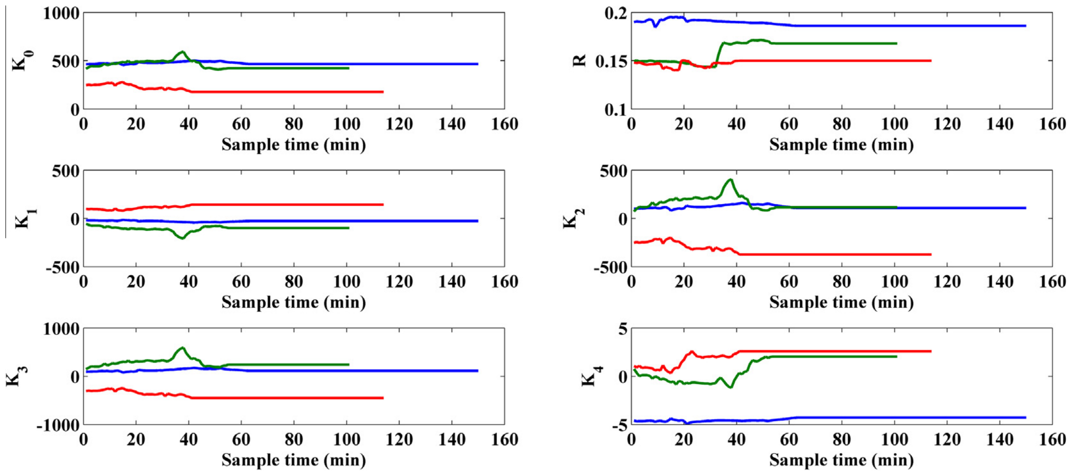

Fig. 4. Results of parameters identification (three discharge processes of three different vehicle, data collection periods: 2011-06-02 08:24:25–2011-06-02 11:02:11 (blue line), 2011-06-02 09:07:46–2011-06-02 10:50:22 (green line), 2011-06-02 13:33:12–2011-06-02 15:28:59 (red line)). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Comparative analysis of parameters

Section 4.3 gives the identification of one discharge process. In order to more detailedly discuss characteristic of each parameter and real-time performance of identification, we choose more experimental data collected from three discharge processes of three different vehicles to respectively identify parameters. The results are shown in Fig. 4.

The analysis of results of parameters identification is below:

(1) The physical meaning of the parameter R is the battery resistance. In theory, R is a fixed value. The result shows the value of R just has altered insignificantly (0.15–0.2). And in all experiments $R > 0$ also points out all experimental data collect from the discharge processes.
(2) The values of the other parameters except R have great difference under different experimental data. The values for parameters k_1, k_2, k_3, k_4 may even change between negative and positive.
(3) In conclusion, the battery condition, the vehicle running status and the traffic have very significant effect on the above results. Therefore, it's necessary to on-line identify parameters and estimate SOC.

Particle filter

An outline of particle filter

PF is a nonlinear filter employing Monte Carlo Sampling method to solve integration problem in Bayesian estimation. The nonlinear filter problem is to recursively calculate the value of state vector z_k at time k. The set of system output y_i measurements at time k is $y_{0:k} = \{y_i : i = 0, 1, \ldots, k\}$. The state space model of the dynamic system is described in Eq. (3), in which w_k is white process noise and v_k is measurement noise (usually but not necessarily assumed to be white) (Doucet et al., 1993).

The solution of probability density function (pdf) is the main idea of PF. The value of the posterior pdf $p(x_k|y_{0:k})$ can be calculated according to two steps (prediction and update) in Bayesian estimation. The prediction step is to calculate the prior pdf.

$$p(x_k|y_{0:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|y_{0:k-1})dx_{k-1} \tag{19}$$

The update step is to update the prior pdf via Bayesian' rule.

$$p(x_k|y_{0:k}) = \frac{p(y_k|x_k)p(x_k|y_{0:k-1})}{\int p(y_k|x_k)p(x_k|y_{0:k-1})d_{x_k}} \tag{20}$$

where, $p(x_k|x_{k-1})$ is determined by the state equation and $p(y_k|x_k)$ is likelihood function determined by the observation equation.

Since it is very difficult for both nonlinear and non-Gaussian system to solve the integration, sequential importance sampling (SIS) which is one of Monte Carlo method is used in Bayesian estimation. So, the posterior pdf is

$$p(x_k|y_{0:k}) \approx \sum_{i=1}^{N} \tilde{w}_k^i \delta(x_k - x_k^i) \tag{21}$$

$$\tilde{w}_k^i = \frac{w_k^i}{\sum_{i=1}^{N} w_k^i} \tag{22}$$

$$w_k^i = w_{k-1}^i \frac{p(y_k|x_k^i)p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{k-1}^i, y_k)} \tag{23}$$

where, w_k^i is the weight of each particle and $\tilde{w}_k^i$ is the normalization. $\delta(\cdot)$ is Delta Function. x_k^i is sampled from the important distribution function $q(x_k^i|x_{k-1}^i, y_k)$. N is the number of particles.

When the important distribution function is closer to the real posterior probability density function, the performance of estimation is more accurate. However, the common problem is the degeneracy phenomenon in PF. Therefore, the resampling used to efficiently solve the problem is investigated to estimate SOC in the paper. The resampling is to eliminate particles with the small weights and concentrate more on particles with large weights. A new particle set $(x_k^{i^*})_{i^*=1}^{N}$ is generated by resampling N times from $p(x_k|y_{0:k})$ and the weights are reset to $w_k^j = \frac{1}{N}$ (Arulampalam et al., 2002) (Geweke, 1991). More details on the reduction of PF and resampling are in Daum (2003), Doucet et al. (1993), Daum (2005).

Steps of particle filter

- Step 1: Initialization
  Set the iteration variable $k = 0$. For $i = 1, 2, \ldots, N$, particle set $\{x_0^i, w_0^i\}$ is obtained from the initial distribution $p(x_0)$.

- Step 2: Particle sample

  For $i = 1, 2, \ldots, N$, sample $x_k^i \sim q(x_k|x_{k-1}^i, y_k)$.

- Step 3: Weight update

  Using Eq. (23), the weight is computed. The normalization of weight $\tilde{w}_k^i$ is calculated according to Eq. (22). Whether the particles need to resampling. If yes, go to Step 4. If no, go to Step 5.

- Step 4: Resampling

  Assign sample: $x_k^{i^*} = x_k^j$. Assign weight: $\tilde{w}_k^j = \frac{1}{N}$.

- Step 5: State estimation

  The estimated state is given as

$$\hat{x} = \sum_{i=1}^{N} \tilde{w}_k^i x_k^i \tag{24}$$

- Step 6: End
  k is increased by itself and return to step 2 until iteration ends.

Experimental results of SOC estimation

Overview of SOC estimation

The general overview of SOC estimation: after on-line identified by RFF at the each iteration, the new estimated parameters are input into the proposed battery model and then SOC is estimated by PF. But after the criterion of ending identification runs, the new parameters are constant values at the following iterations. So then, we skip the step of identification and directly use these constant parameters.

Parameters and structure determination

The proposed battery model in Eq. (3) is considered as the state space model of PF. The state vector z_k represents SOC. The measured input vector i_k and output vector y_k represent respectively the battery current and the battery voltage. The parameters of model k_0, R, k_1, k_2, k_3, k_4 are on-line determined by RFF. The RMSRE and RE are used to evaluate the accuracy of estimation.

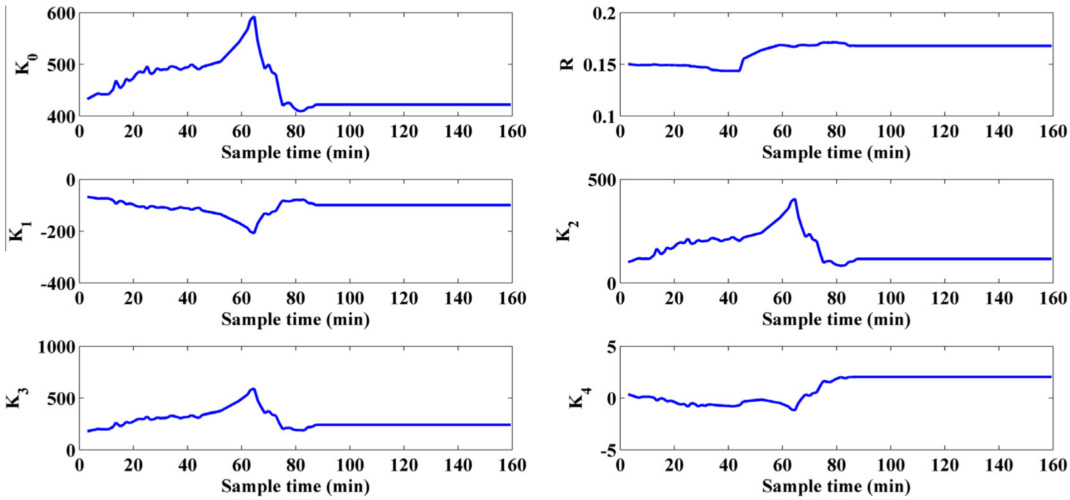

Fig. 5. Parameters Identification.

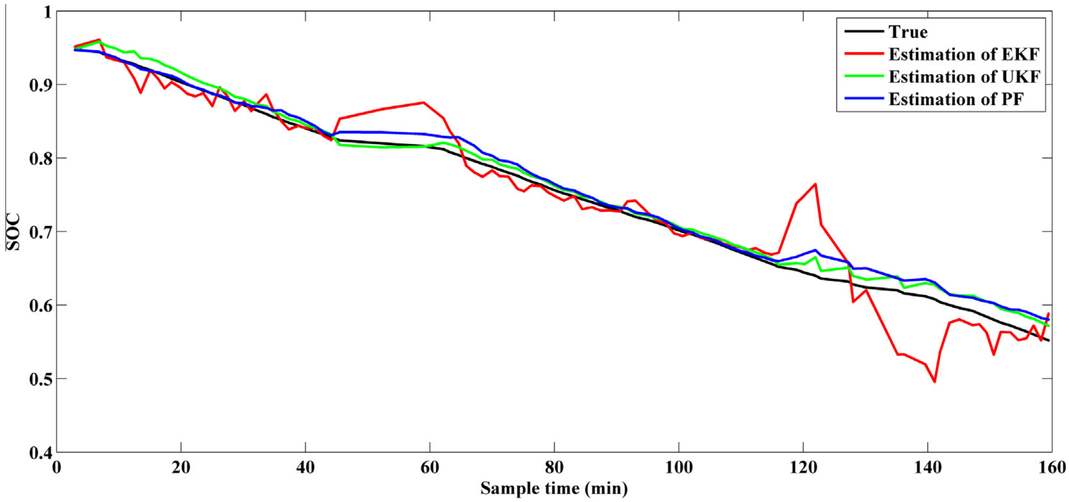

Fig. 6. SOC estimation based on PF, UKF and EKF.

Results

Firstly, the experiment of SOC estimation which data collected from one discharge processes running from 13:52 pm to 16:30 pm on May 30, 2011 is carried out. For the purpose of better analyzing the performance of SOC estimation based on PF, we also give comparison of three nonlinear filters (PF, UKF and EKF). The results of identification and estimation are respectively shown in Figs. 5–7.

Moreover, data collected from four different discharge processes of the same vehicle are used to estimate SOC. RMSRE is treated as the error indicator and the results are shown in Table 3.

This paper evaluates the performance of three nonlinear filters estimating SOC through two aspects: accuracy of estimation and computational complexity.

(1) The Figs. 6 and 7 and Table 3 show the error results of three nonlinear filters are both small and within the engineering allowance. However, PF provides a significant improvement relative to EKF and UKF.
(2) Computational complexity is a key issue for nonlinear filters in application. The computational complexity of EKF with d - dimensional state vector is $o(d^3)$ and the computational complexity of UKF is the same as EKF (Daum, 2005). Moreover, the computational complexity of PF has a problem: the curse of dimensionality (Daum, 2003). For low dimensions, PF can achieve better estimation accuracy with a computational complexity roughly the same as EKF.

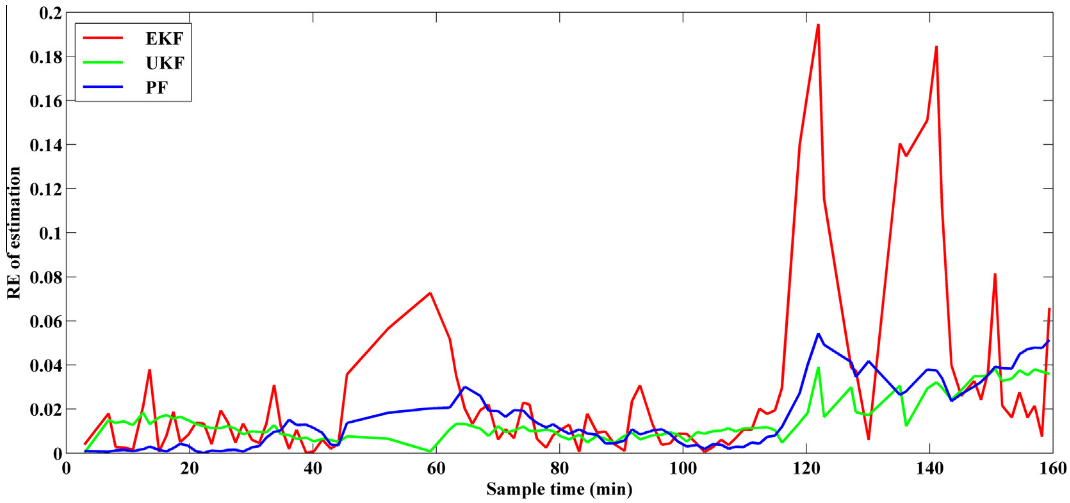

Fig. 7. The error results of SOC estimation based on PF, UKF and EKF.

Table 3
The error results.

Discharge processes	Data collection period	RMSRE		
		PF	UKF	EKF
1	2011-05-25 06:15:07 2011-05-25 10:17:25	0.0157	0.0169	0.0501
2	2011-05-28 09:08:01 2011-05-28 12:17:15	0.0206	0.0251	0.0303
3	2011-05-27 13:04:29 2011-05-27 17:03:32	0.0125	0.0158	0.0233
4	2011-06-01 09:20:18 2011-06-01 11:42:19	0.0105	0.0208	0.0312
Average		0.0148	0.0197	0.0337

However, for high dimensions, the computational complexity of PF is enormous. In this paper, the state vector only has one state variable, therefore SOC estimation based on PF belongs to low dimensional problem and thus the computational complexity of PF are as same as EKF and UKF.

Conclusion

This paper proposes a mathematical battery model and identifies the unknown parameters in the battery model using the recursive least square with forgetting factors. The experimental results of identification suggest the estimated parameters match with the practical battery model. Although the proposed battery model does not discuss the battery temperature, state of health (SOH) and battery aging, we can consider that the influence of three battery parameters is reflected in the battery resistances. In the future, the consideration of the relationships among more battery performances and SOC can be investigated.

After the unknown parameters are identified, the proposed battery model is regarded as state space model of PF. Then, SOC is estimated by PF. In conclusion, the contrastive experiments of three nonlinear filters (PF, UKF and EKF) confirm the validity and better performance of using PF to estimate SOC under same computational complexity. SOC estimation is a key point for obtaining the remaining operational time or the remaining range in the running EV. Good estimated remaining operational time or remaining range can contribute to users' travel planning and scheduling. A complex relationship (often nonlinear) exists among SOC, the remaining operational time and the remaining range. This issue can be more researched in the future.

All experimental data are collected from EVs with Li-ion batteries operating in Beijing. Although all experimental data come from Li-ion batteries, we believe the proposed method can be applied in other battery applications such as NI–MH and lead-acid. The issue can give future directions of research.

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